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Session X. Airborne Doppler Radar / NASA

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Signal Processing Techniques for Clutter Filtering & Wind Shear Detection
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**SIGNAL PROCESSING TECHNIQUES
for
CLUTTER FILTERING
and
WINDSHEAR DETECTION**

**E. G. Baxa, Jr.
CLEMSON University**

3rd CMTAW meeting

**Radar Systems Laboratory
Electrical and Computer Engineering
Clemson University**



Oct. 18, 1990

Signal Processing Techniques for Clutter Filtering and Windshear Detection

E. G. Baxa, Jr., Clemson University

ABSTRACT

It has been argued that the windshear hazard factor is a sufficient statistic for detecting hazardous windshear conditions. The hazard factor is computed by estimating the spatial gradient of windspeed across the radar sector of coverage. With the airborne Doppler radar, one approach is to use estimates of windspeed within each range resolution cell as a basis for estimating this spatial gradient. Currently, research is directed at understanding how to obtain the best possible estimate of windspeed conditions within a range cell. Conventional pulse-pair processing obtains mean estimates of windspeed. The presence of strong ground clutter in a low altitude airborne radar return can significantly bias these mean estimates. One thrust of this effort has involved use of adaptive clutter rejection filters based upon auto-regressive modelling of the ground clutter returns. This offers the potential for using very simple finite impulse response digital filters to eliminate highly specular ground clutter returns. For situations where the weather return is quite low, e.g., the "dry" microburst, clutter rejection filtering can reduce the weather return signal levels to the extent that the variance of the mean estimates is quite large. Research is involved with using mode estimates, i.e., estimates of the most probable windspeed, in each range cell in determining the hazard factor. An extended Prony algorithm is discussed. It is based upon modelling the radar return as a time series and appears to offer potential for improving hazard factor estimates in the presence of strong clutter returns.

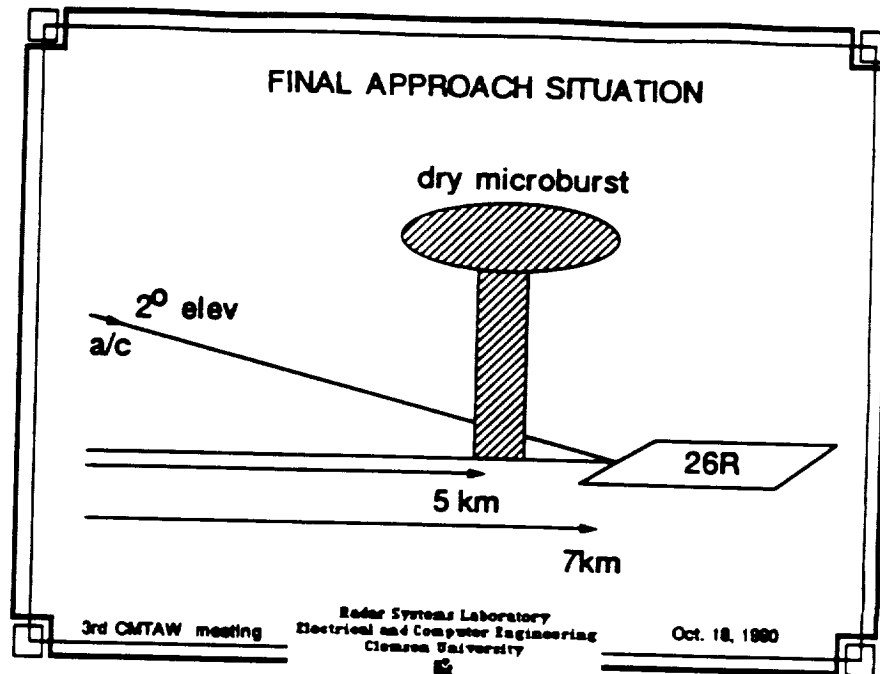
INTRODUCTION

- Hazard factor proportional to windspeed spatial gradient
 - Windspeed gradient can be estimated using a "characteristic" windspeed estimated in each range cell
- MEAN - statistical average
MEDIAN - middle of ordered frequency content
MODE - most probable value
- Pulse-pair estimate is a MEAN estimator
 - What are the problems with MEAN estimation?
Are there meaningful alternatives?



PRESENTATION HIGHLIGHTS

- MEAN estimates can be biased in low signal-to-clutter ratio environments. Also unstable.
- Clutter rejection filtering may be counter productive in low SCR environments: reduced sensitivity, phase jitter effects
- MODE estimation through process modelling from IQ data may overcome problems with bias in the MEAN estimates
- Signal/clutter process modelling has limitations in low signal-to-noise environments

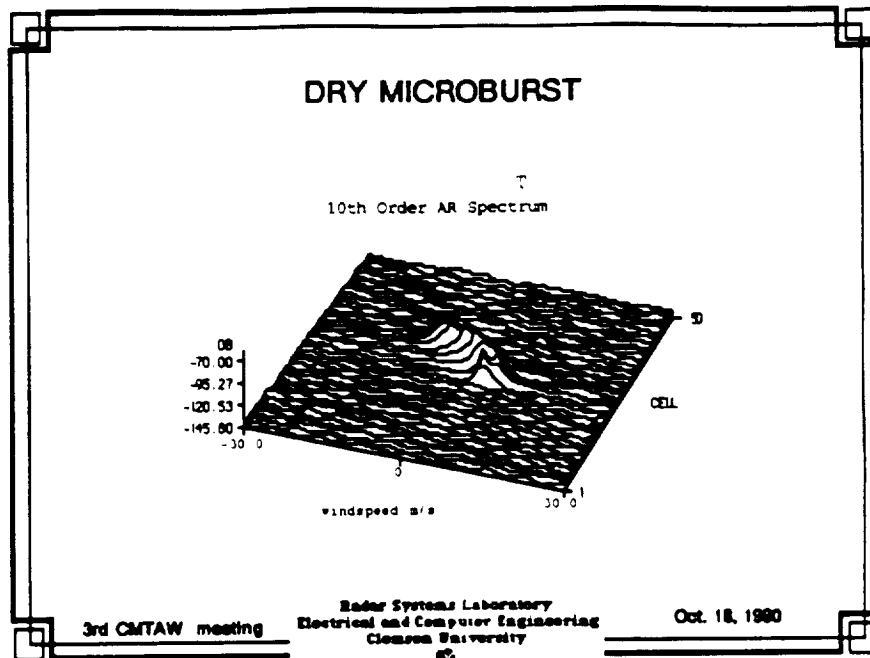


Notes

Simulated final approach situation with A/C on 3 degree glideslope and radar antenna elevated 2 degrees. Dry microburst in front of Denver runway 26R.

Ground clutter return is based upon SAR data taken at Denver Stapleton airport.

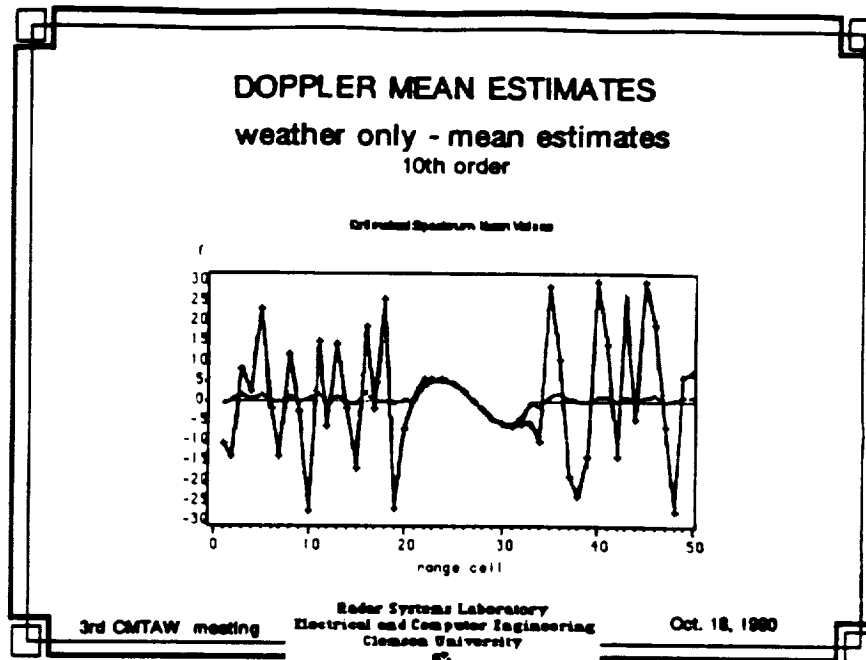
Signal to clutter ratios are on the order of 0 dB in the range cells in which the microburst is present.



Notes

Auto-regressive model determined spectrum in each of the fifty range cells with the simulated "dry" microburst without any clutter present. Signal-to-noise ratios in the range cells with the microburst varies from 0 to 30 dB.

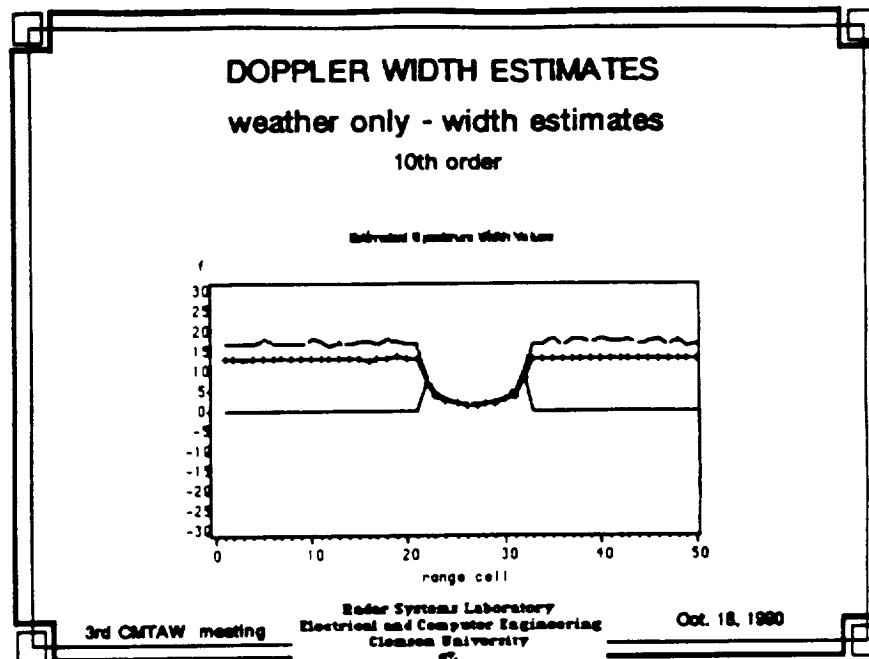
Note: zero windspeed corresponds to zero Doppler relative to the ground speed of the aircraft. Positive windspeed corresponds to winds toward the aircraft and negative is away from the aircraft. Range cells are 150 m.



Notes

- Mean windspeed estimates considering simulated "dry" microburst without ground clutter. Five different mean estimates are used:
1. pulse-pair computed in the time domain
 2. pulse-pair computed in the frequency domain using an AR spectrum estimate
 3. Fourier domain mean estimate
 4. AR spectrum domain mean estimate
 5. First order AR model pole estimate

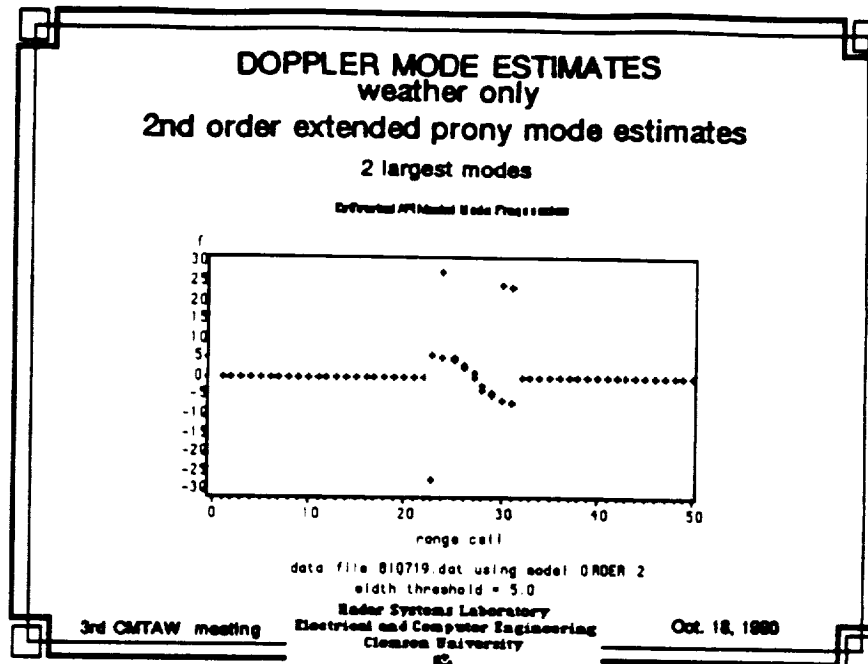
Note: The microburst appears in range cells 20-33 (approximately). Some estimates of mean have been edited to zero outside this range based upon estimated signal to noise ratio in return.



Notes

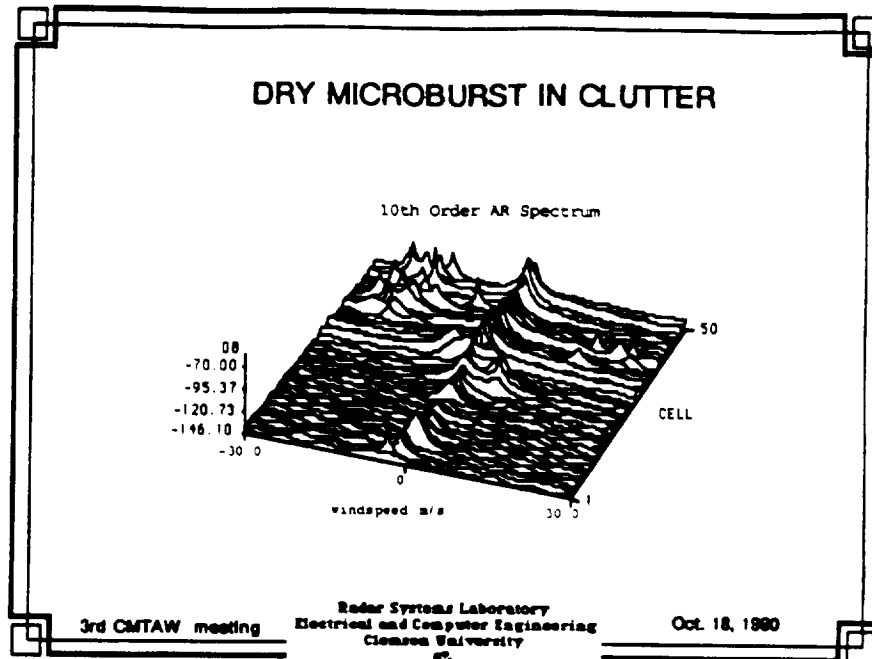
- Width estimates for the situation in the previous slide. Four different width estimators have been used:
1. pulse-pair width computed in the time domain.
 2. pulse-pair width computed in the AR spectrum frequency domain.
 3. AR spectrum standard deviation
 4. First order AR model coefficient

Note: Some width estimates for range cells outside those containing the microburst have been edited to zero because of low signal to noise ratio estimates.



Notes

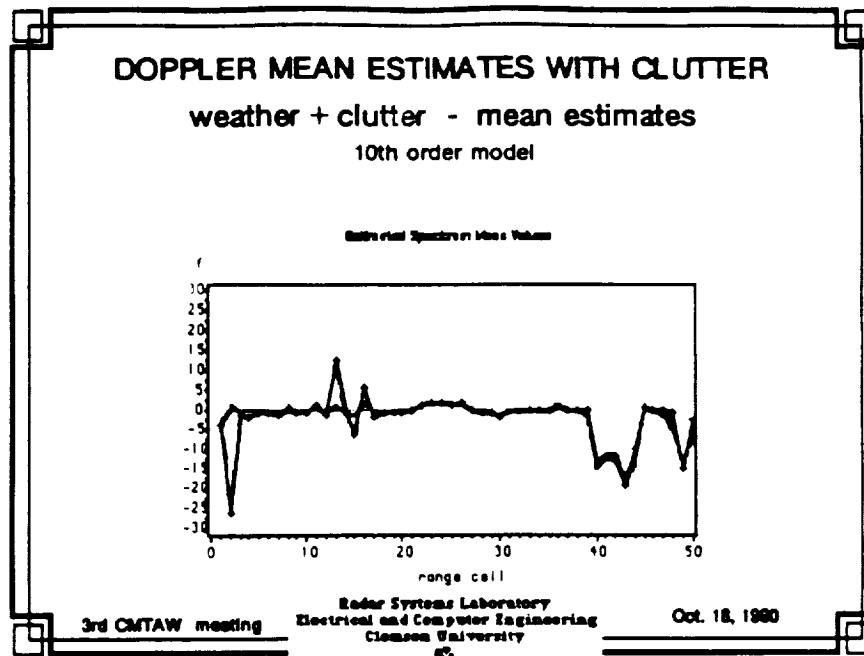
Spectrum mode estimates using an extended PRONY algorithm based upon a second order AR model of the data. Outliers are caused by insufficient model order.



Notes

AR model determined spectrum in each of the fifty range cells with the "dry" microburst and ground clutter present in the return. No clutter rejection filtering is used. Ground clutter in the range cells 40-50 in the negative Doppler region is associated with an interstate highway included in the simulation. Signal to clutter ratios are on the order of 0 dB.

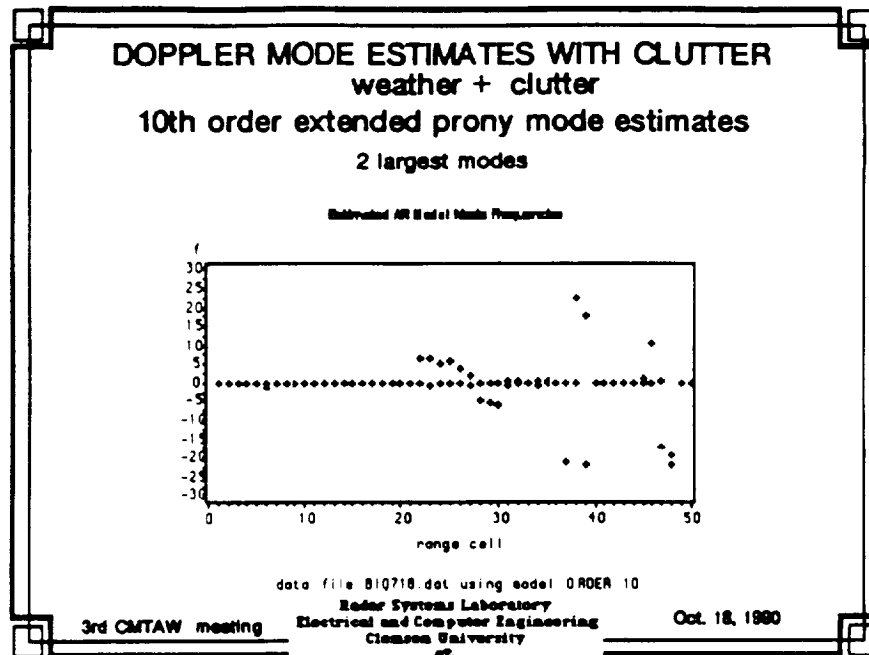
Note that the microburst can still be identified.



Notes

Mean estimates without clutter rejection filtering for the situation depicted in the previous slide. The same five estimators used previously are included. Again some of the mean estimates have been edited to zero based upon signal to noise ratio estimates of the return.

Note that the clutter biases the mean estimates in the range cells 20-33 so that the presence of the macroburst is no longer evident.

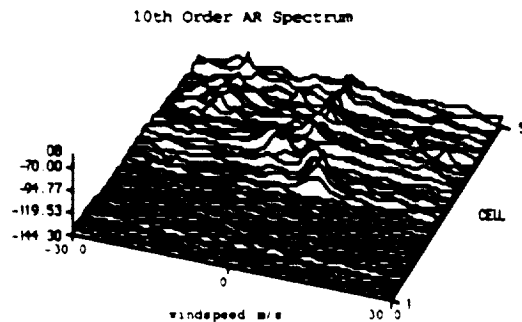


Notes

Spectrum mode estimates using an extended PRONY algorithm based upon a tenth order AR model of the data. Only the two strongest modes within each range cell are retained. Outliers are caused by the presence of discrete clutter (e.g. interstate highway)

Note that the microburst spectrum modes are clearly identifiable even though no clutter rejection filtering has been done.

DRY MICROBURST WITH OPTIMAL CLUTTER FILTER



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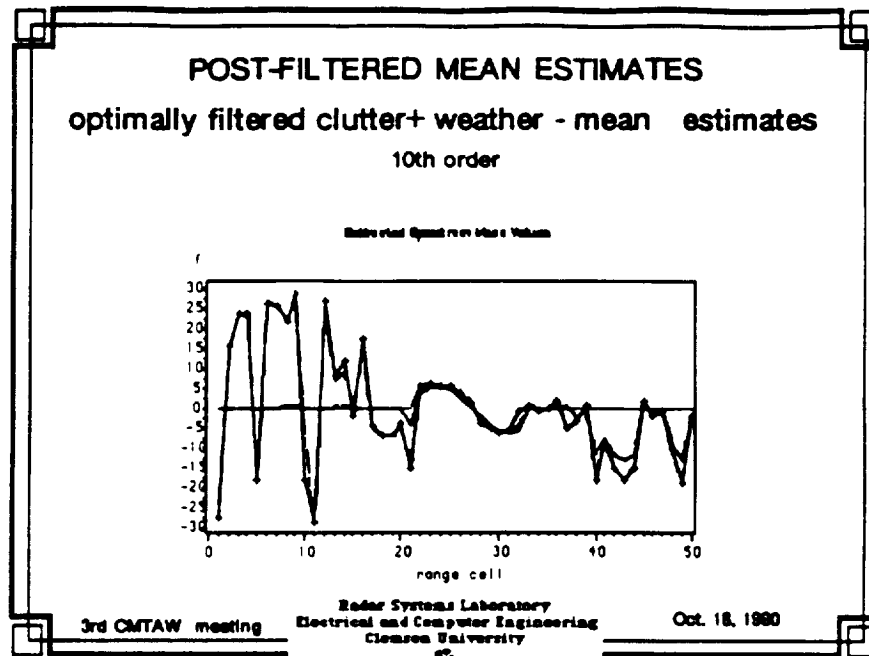
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Notes

AR model determined spectrum in each of the fifty range cells with the radar return pre-processed with an optimum clutter rejection filter in each range cell. The filter in each range cell is based upon a tenth order AR model generated FIR filter which is adaptively determined using simulated clutter-only data for the situation depicted earlier.

Note the microburst is clearly present and some of the discrete clutter in later range cells is not completely eliminated.

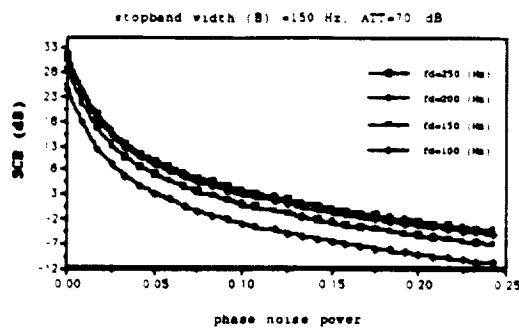


Notes

Mean estimates with optimum clutter rejection filtering. The same five mean estimators used previously are compared. Again some of the mean estimates have been edited to zero because of low signal to noise ratio estimates.

Note that the microburst can be clearly identified.

PHASE NOISE EFFECTS ON CLUTTER FILTERING



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Notes

Radar system pulse-to-pulse phase jitter is analyzed in the presence of the low signal to clutter ratio situation.

Here an ideal notch filter centered at zero Doppler with a stopband width of 150 Hz and 70 dB stopband attenuation is analyzed. The prefiltered signal to clutter ratio is held to -30 dB and the weather mean Doppler is varied from 100 to 250 Hz. As the phase jitter noise is increased the clutter spectrum is spread to the point that the rejection filter will not provide enough signal to clutter ratio gain for reliable pulse pair processing.

SUMMARY

- Characterization of windspeed within a radar range resolution cell can be severely limited by ground clutter returns
- Low level weather returns will present the greatest challenge in Hazard detection
- Signal processing needs include a variety of algorithms and may require super-computer processing loads for real time implementation

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Notes

Characterization of ground clutter returns in initial flight tests will be of paramount importance.

A suite of signal processing algorithms will be needed to improve confidence in hazard detection

Airborne radar will be important for hazard detection but should be integrated with other sensor types.

Bibliography

1. E. G. Baxa, Jr. and J. Lee, "The Measurement of Windspeed Gradient with Low PRF Radar," Proc. Southeast. Symp. on Sys. Theory, SSST-88, Charlotte NC, March 1988.
2. J. Lee and E. G. Baxa, Jr., "Preliminary Analysis of Windshear Detection Signal Processing Considering Doppler Weather Radar," Radar Systems Laboratory TR No. 8, Research Triangle Institute subcontract 4-414U-3042 under NASA contract NAS1-17639, Clemson University, September 1988.
3. E. G. Baxa, Jr., "Resolution of the STUSE Algorithm Used in Spectrum Estimation," Radar Systems Laboratory TR No. 9, NASA grant NAG-1-928, Clemson University, December 1988.
4. J. Lee and E. G. Baxa, Jr., "Pulse-pair Spectral Estimates in the Presence of Radar Oscillator Phase Jitter," Proc. 21st Southeast. Symp. on Sys. Theory, Florida State University, Tallahassee, March 1989.
5. W. T. Davis and E. G. Baxa, Jr., "Effects of Filtering on Estimating Spectral Moments of Meteorological Doppler Spectra," Proc. 21st Southeast. Symp. on Sys. Theory, Florida State University, Tallahassee, March 1989.
6. W. T. Davis, "The Effects of Clutter-rejection Filtering on Estimating Weather Spectrum Parameters," Radar Sys. Lab. TR no.10, NASA LaRC grant NAG-1-928 and NGT-70055, Clemson University, July 1989.
7. E. G. Baxa, Jr., "On Implementation of the Discrete Fourier Transform - The STUSE Algorithm for Spectral Estimation," IEEE Trans. on Acoust., Speech, and Sig. Proc., vol. 37, no. 11, pp.1763-1765, November 1989.
8. B. M. Keel, "Adaptive Clutter Rejection Filters for Airborne Doppler Weather Radar Applied to the Detection of Low Altitude Windshear," Radar Sys. Lab. TR no.11, NASA LaRC grant NAG-1-928, Clemson University, December 1989.
9. B. M. Keel and E. G. Baxa, Jr., "Adaptive Least Square Complex Lattice Clutter Rejection Filters Applied to the Radar Detection of Low Altitude Windshear," Proc. 1990 IEEE Int. Conf. Acoust., Speech, Sig. Proc., pp.1469-1472, Albuquerque, N.M., April 1990.
10. J. Lee, "Analysis and Improved Design Considerations for Airborne Pulse Doppler Radar Signal Processing in the Detection of Hazardous Windshear" Radar Sys. Lab. TR no.12, NASA LaRC grant NAG-1-928, Clemson University, May 1990.
12. J. Lee and E. G. Baxa, Jr., "Phase Noise Effects on Turbulent Weather Radar Spectrum Parameter Estimation," Proc. 1990 IEEE Int. Radar Conf., pp.345-350, Arlington, VA, May 7-10, 1990.
13. E. G. Baxa, Jr. and J. Lee, "The Pulse Pair Algorithm as a Robust Estimator of Turbulent Weather Spectral Parameters using Airborne Pulse Doppler Radar," (submitted to IEEE Trans. on Aerospace and Elect. Sys.), September 1990.

Estimation of Radial WindSpeed

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Vigyan Inc., Hampton**

Estimation of Radial WindSpeed:

- * From the I and Q data, the mean radial windspeed is determined using Covariance and Spectral domain approaches.
- * Here we study the performance of each of these techniques under varying signal to noise ratio.

Covariance Method:

If $R(\tau)$ is the covariance function of the received sequence then the mean Doppler frequency \hat{f}_d can be estimated by

$$\hat{f}_d \cong \frac{1}{2\pi T_r} \text{Arctan}\left(\frac{\text{Im.}(R(T_r))}{\text{Re}(R(T_r))}\right)$$

The mean radial wind speed is then obtained as

$$\hat{v}_p = \frac{\lambda}{2} \hat{f}_d$$

Spectral Estimation Methods:

If $S(f)$ is the spectral density of the sequence then \hat{f}_d can be estimated by using

$$\hat{f}_d = \frac{\sum_{i=-N/2}^{N/2} f_i S(f_i) W(f_i)}{\sum_{i=-N/2}^{N/2} S(f_i) W(f_i)}$$

where $W(f)$ is the weighting function introduced to suppress the stationary ground clutter which is centered around zero Doppler frequency.

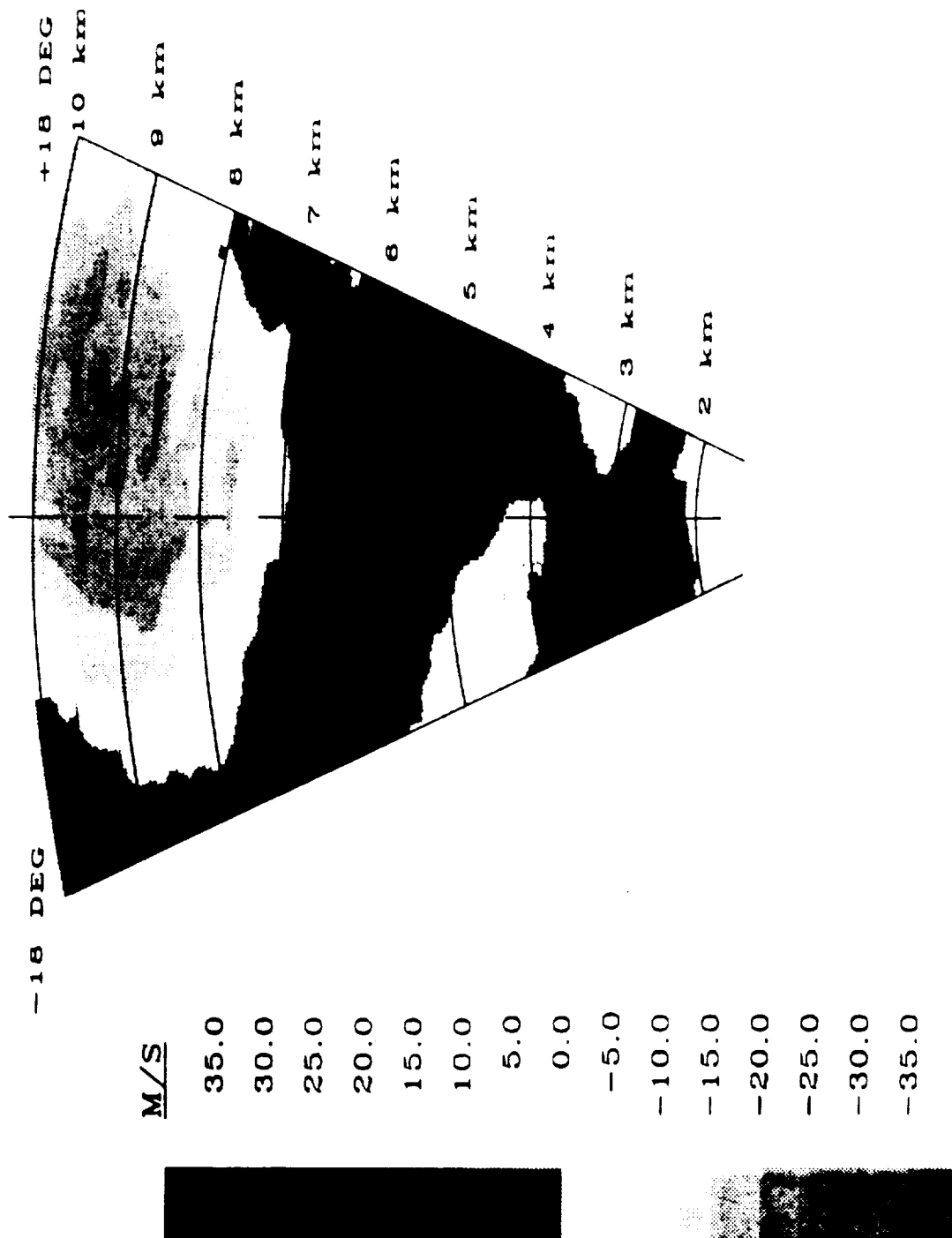
The spectral density $S(f)$ is determined using following methods.

- (1) **Periodogram Method**
- (2) **Forward-Backward Linear Prediction Method**
- (3) **Eigenvector method**
- (4) **MUSIC Method**

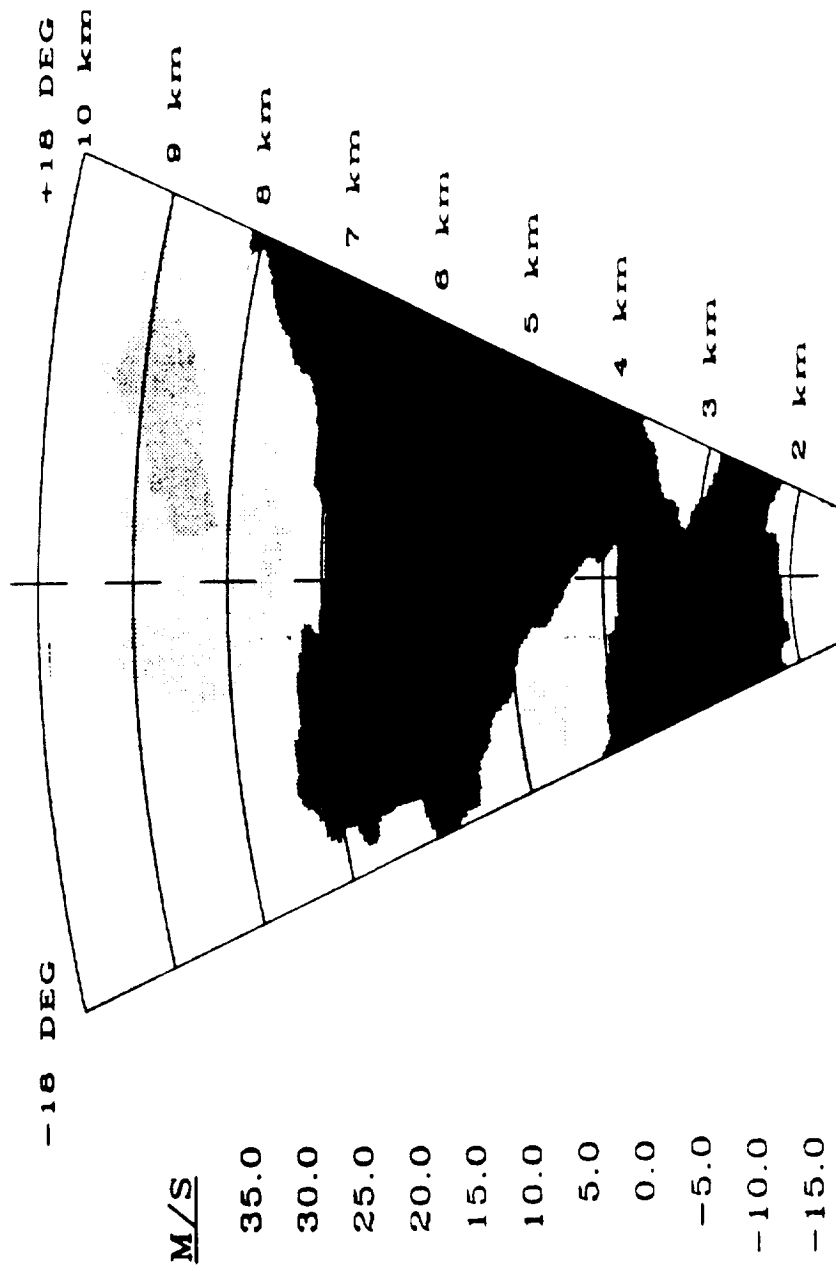
The performance of these methods when the signal to noise ratio is varied between 10 dB to -5 dB is studied

From these results it may be concluded that Covariance method under severe SNR performs better than other methods.

WEATHER RADAR MODEL VELOCITY



WEATHER RADAR MODEL VELOCITY



PULSE PAIR PROCESSOR METHOD (SNR=INFINITY)

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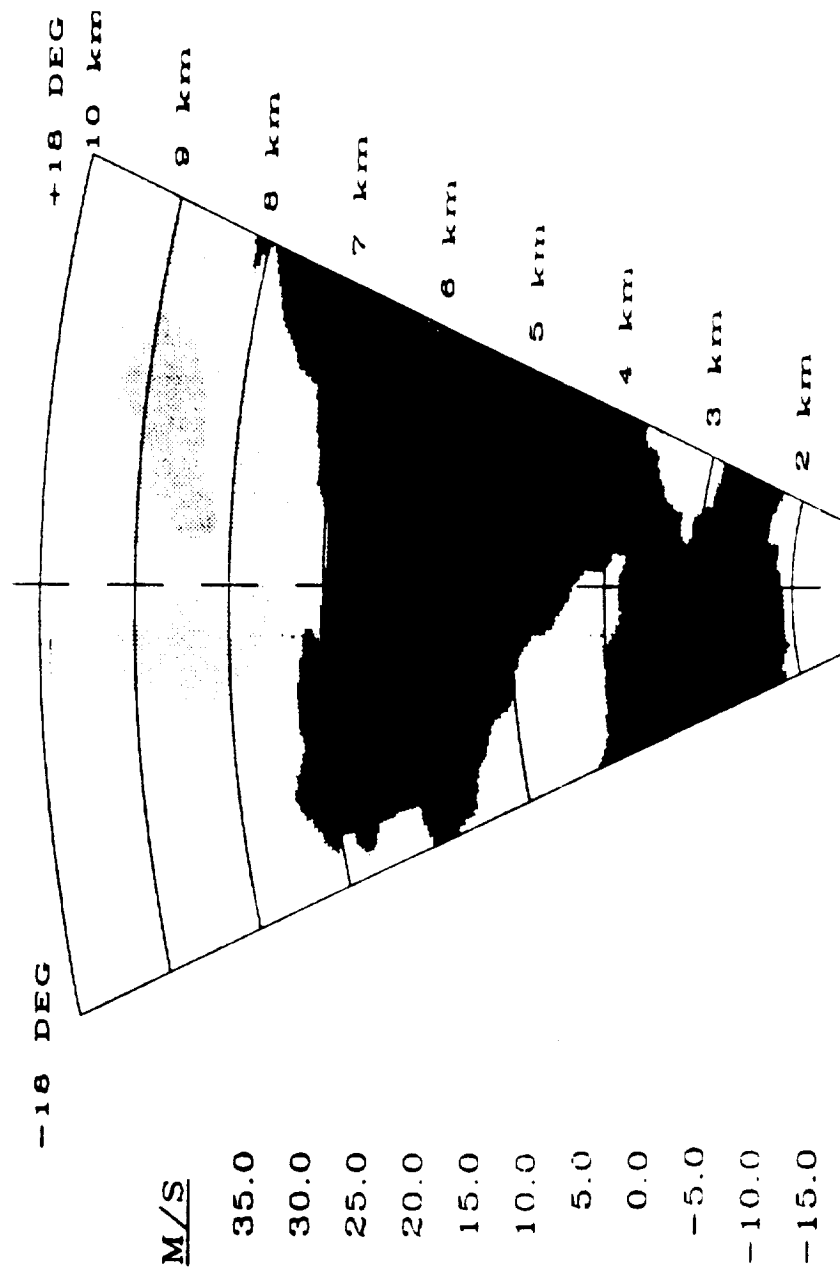
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PULSE PAIR PROCESSOR (SNR=10DB)

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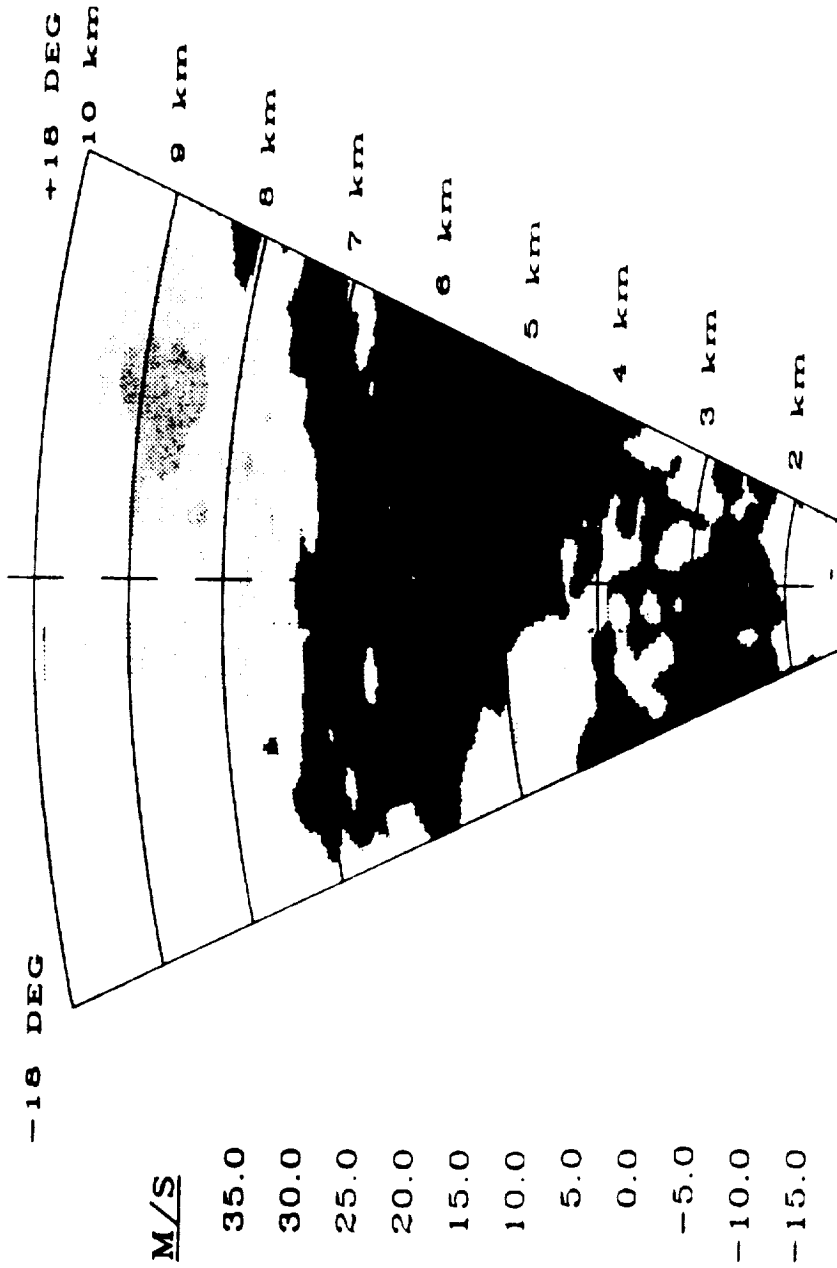
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PULSE PAIR PROCESSOR (SNR=5DB)

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WEATHER RADAR MODEL VELOCITY



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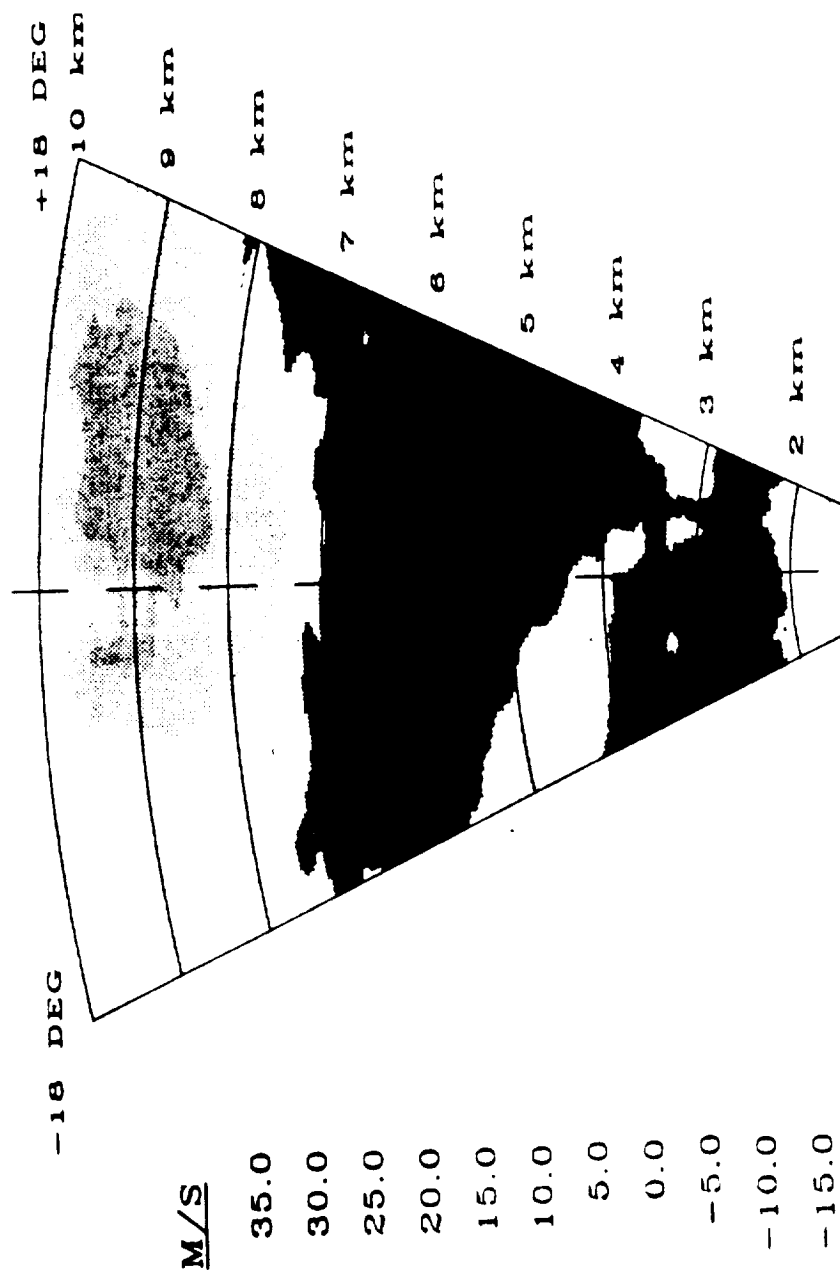
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PULSE PAIR PROCESSOR (SNR=-5DB)

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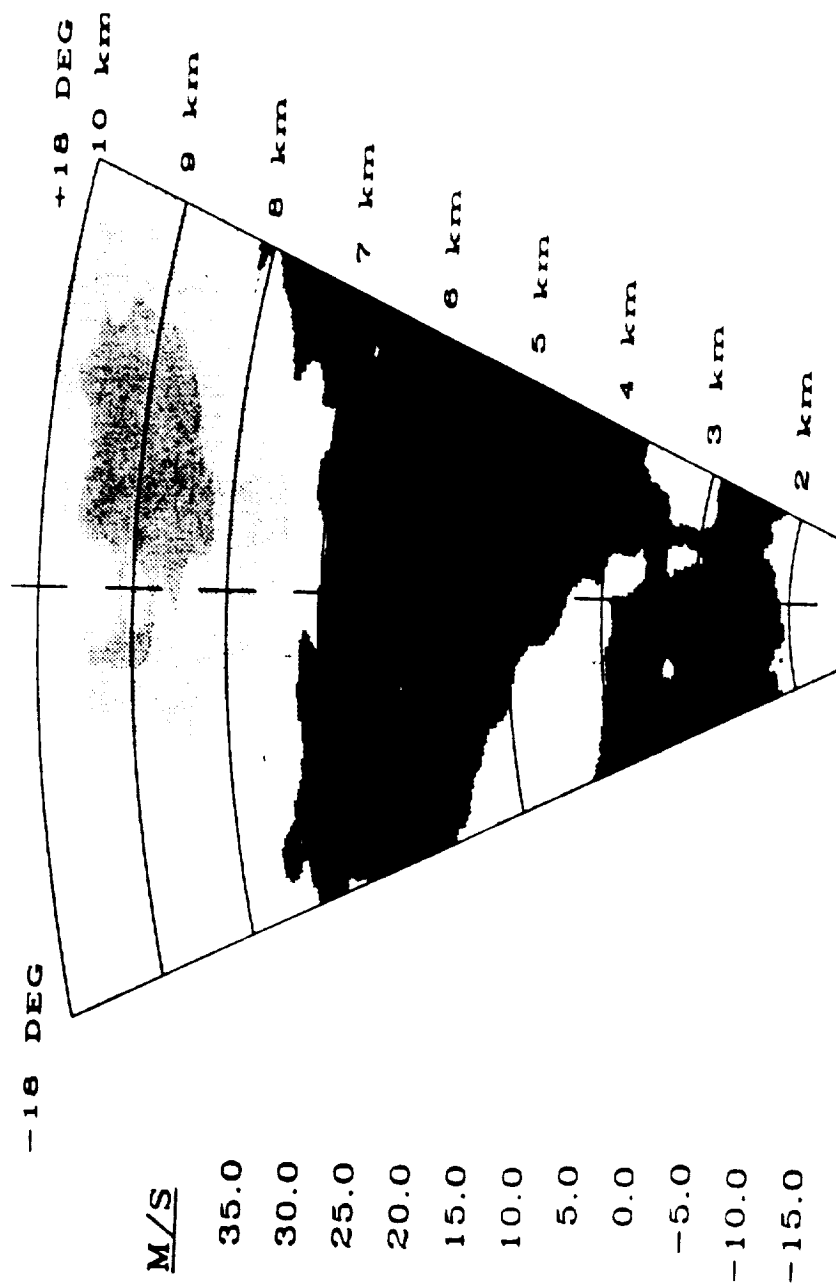
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LINEAR PREDICTOR METHOD (SNR = INFINITY)

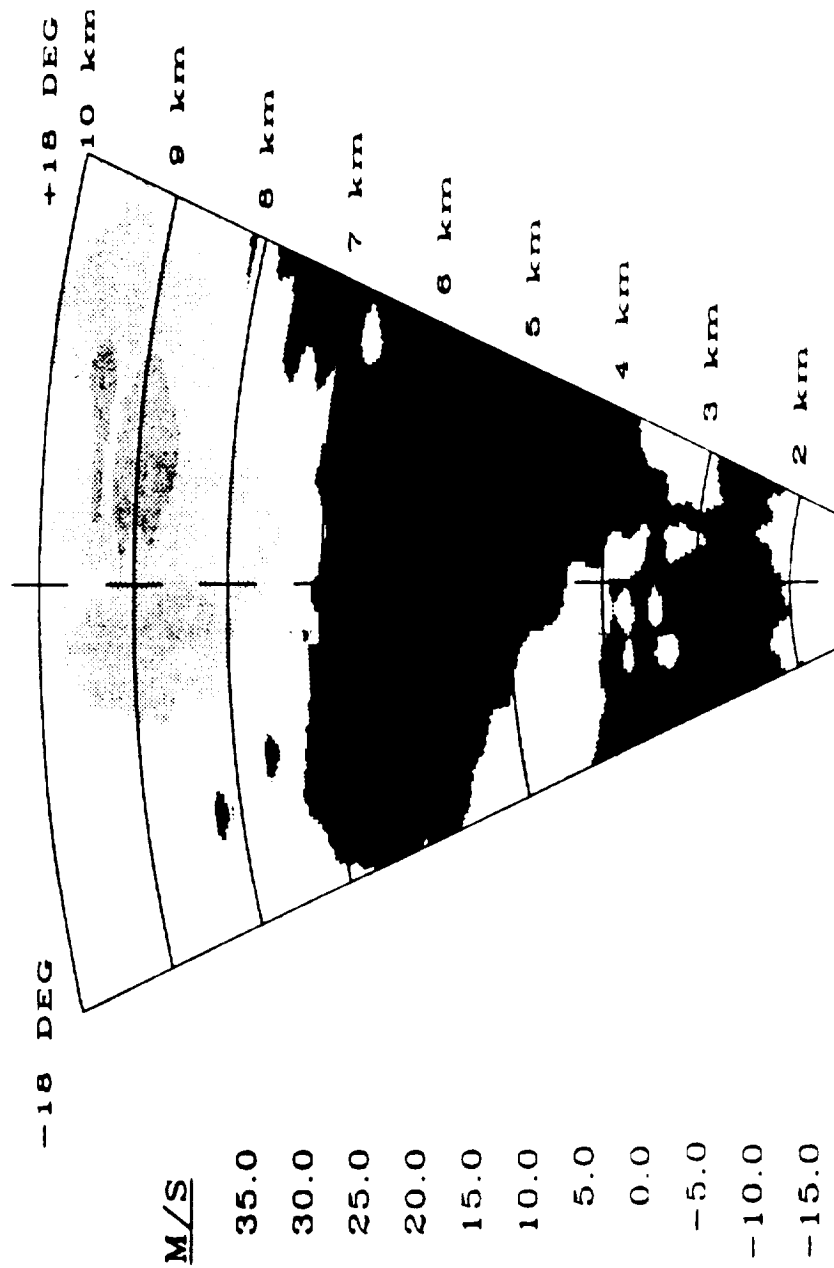
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WEATHER RADAR MODEL VELOCITY



FB LINEAR PREDICTION METHOD(SNR=10DB)

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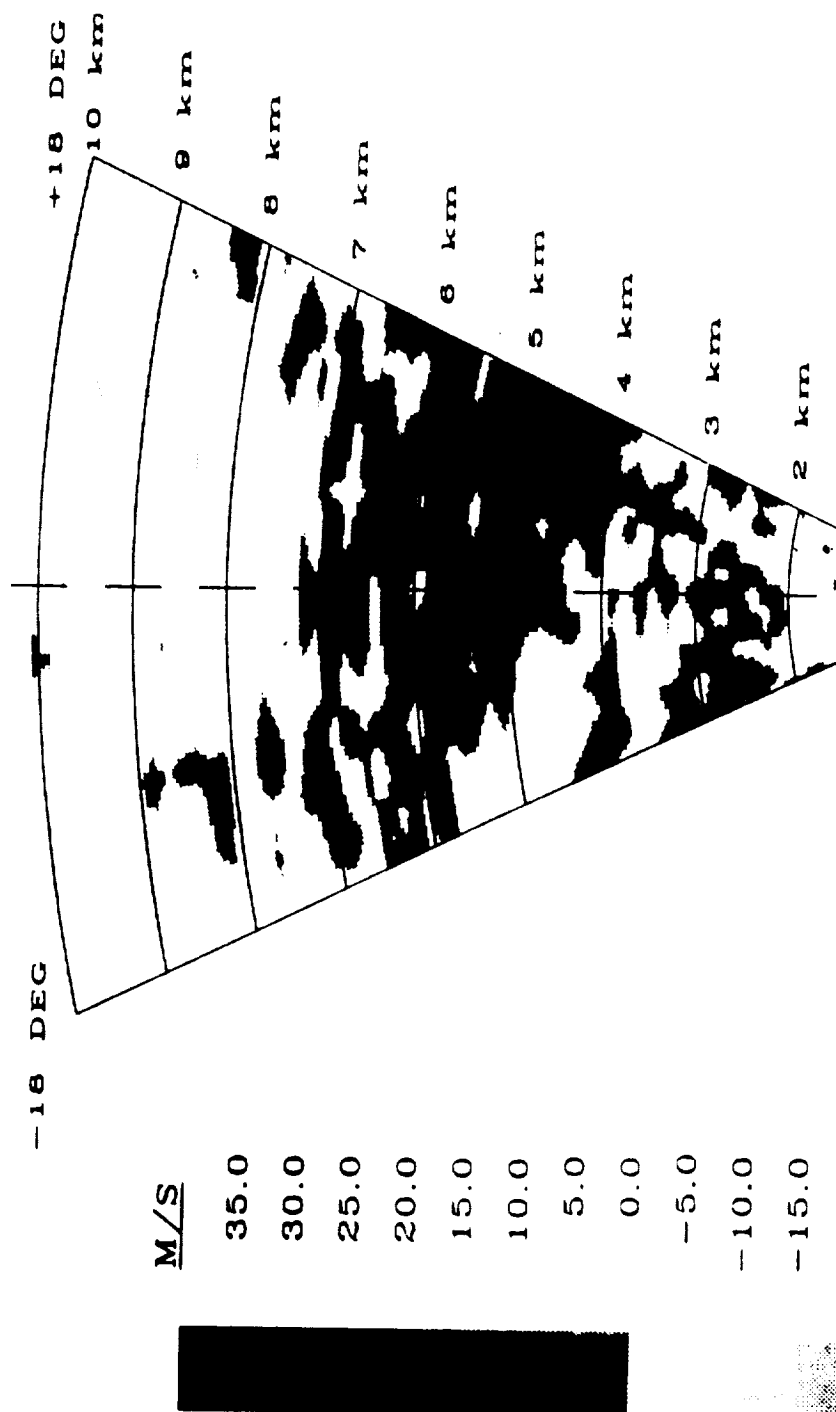
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FB LINEAR PREDICTION METHOD(SNR=5DB)

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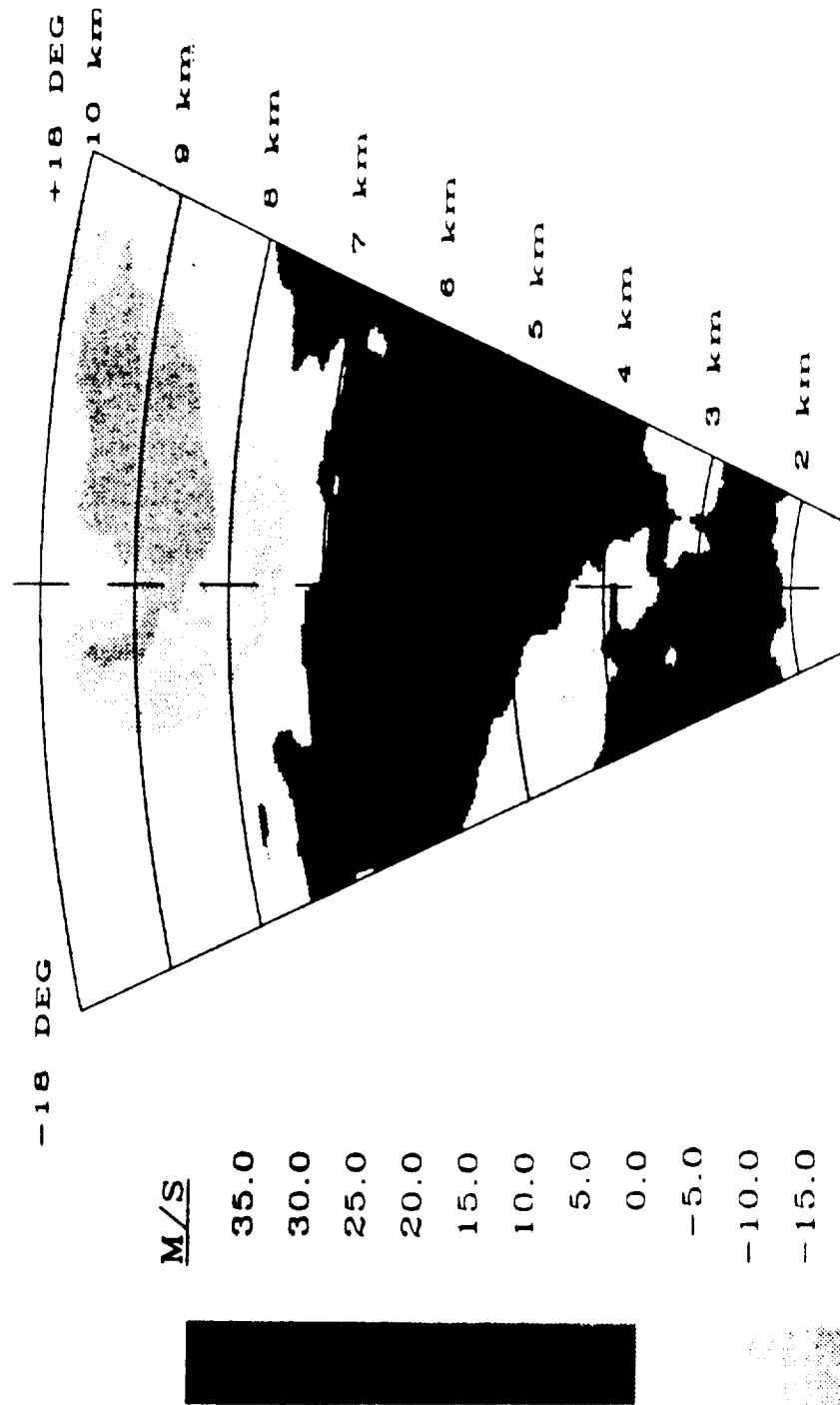
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FB LINEAR PREDICTION METHOD (SNR = -5DB)

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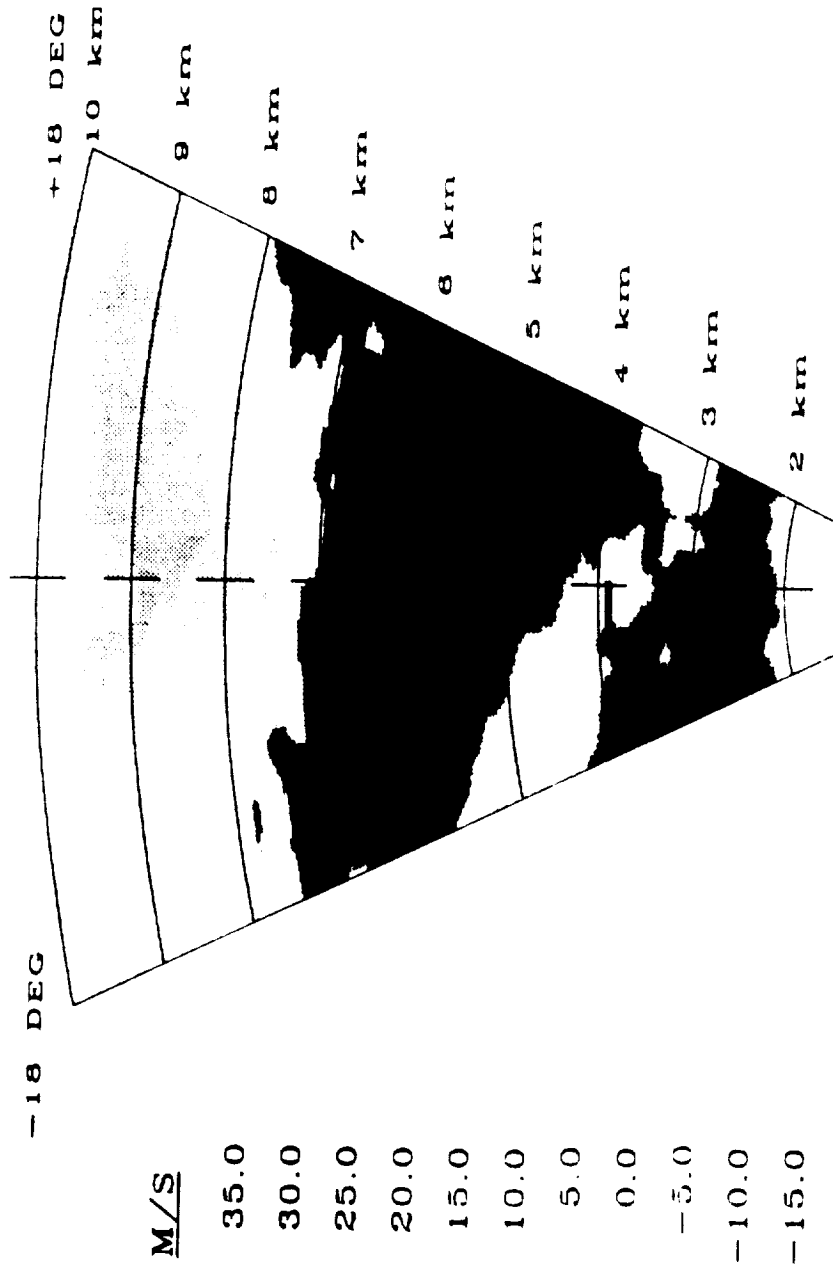
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EIGENVECTOR METHOD (SNR = INFINITY)

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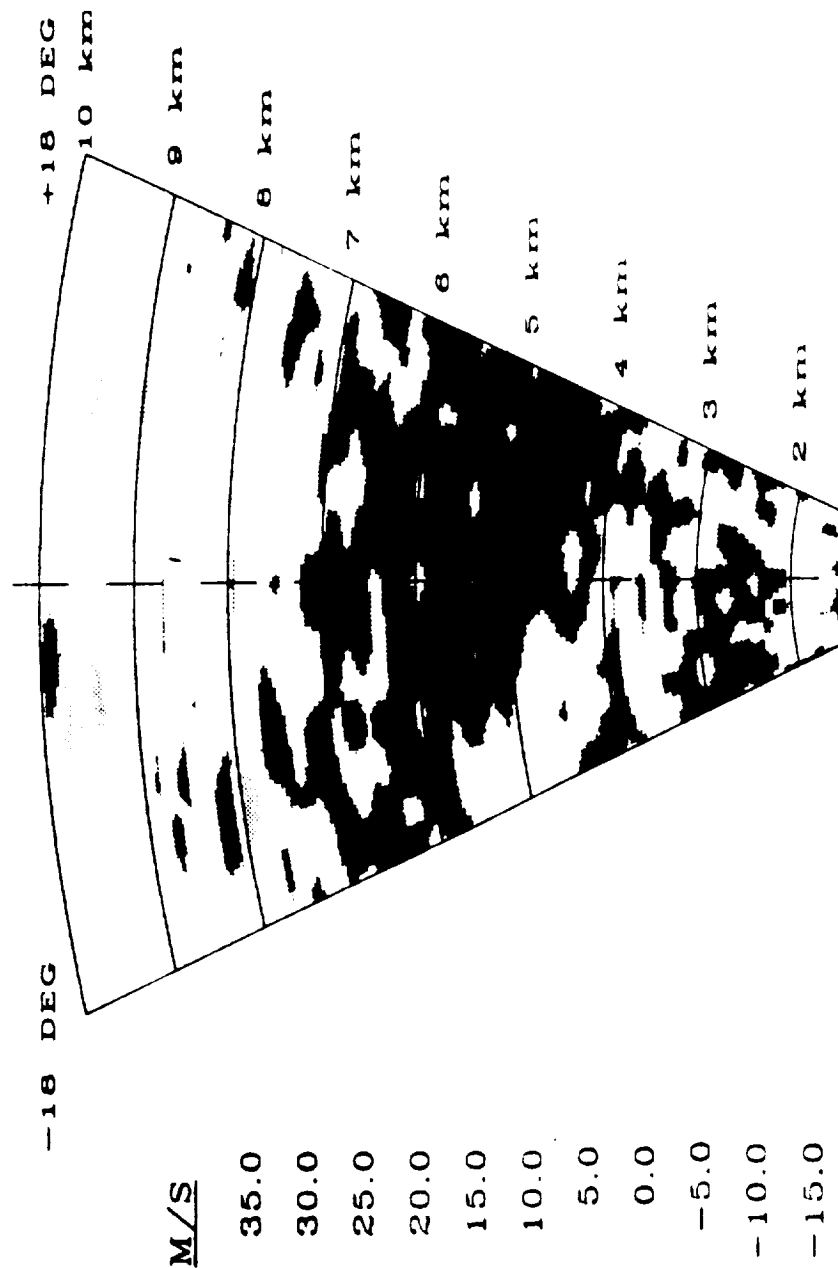
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EIGEN-VECTOR METHOD(SNR=10DB)

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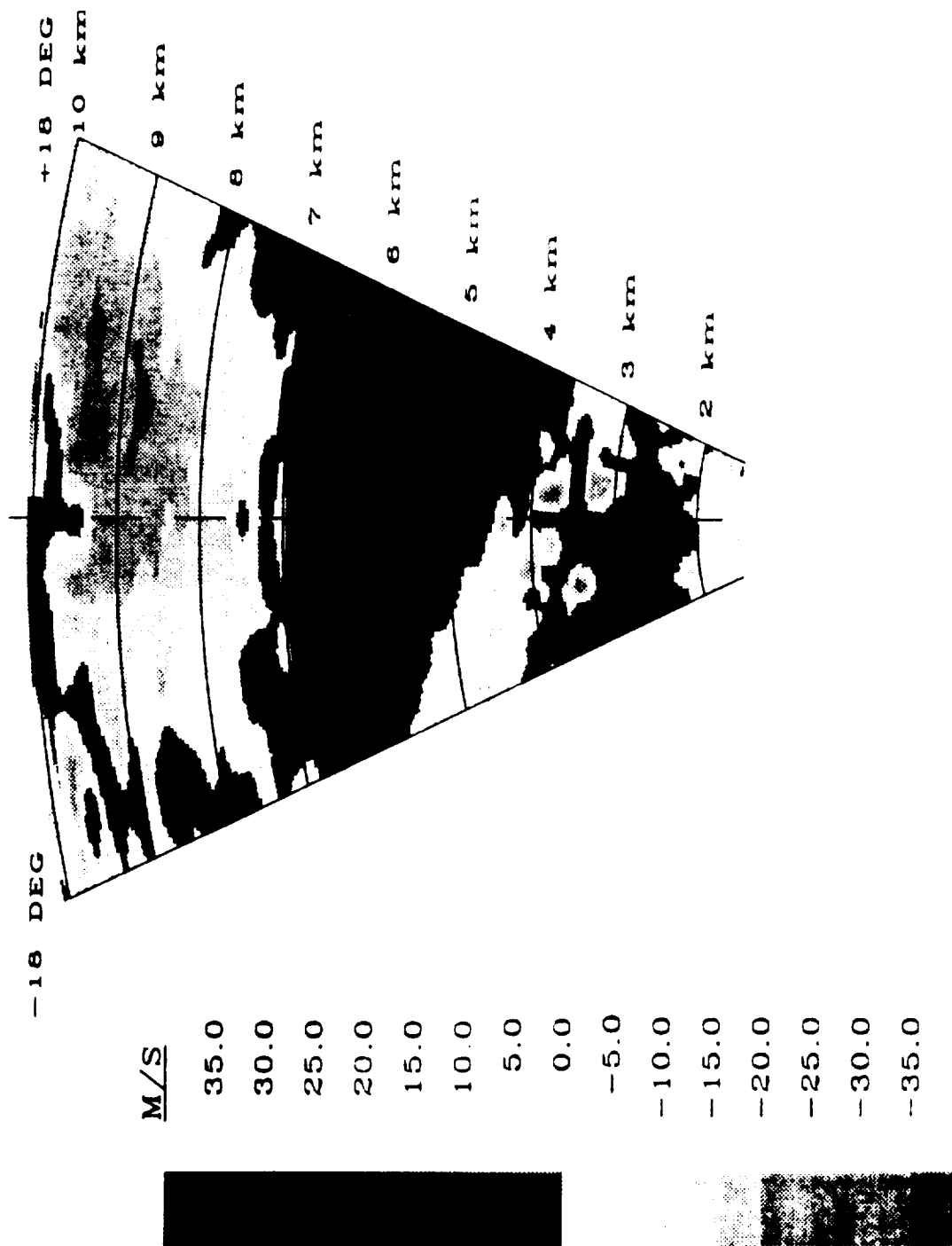
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EIGENVECTOR METHOD (SNR = -5DB)

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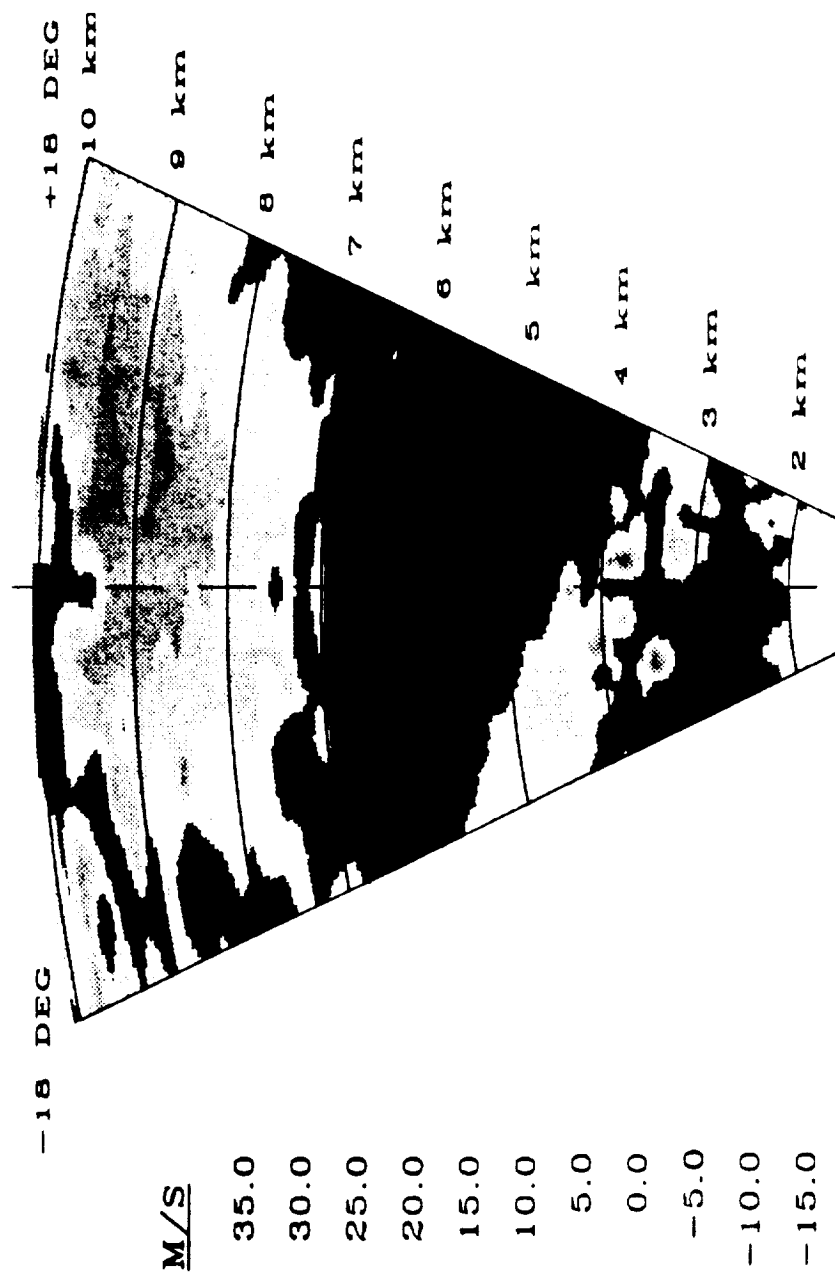
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MUSIC METHOD (SNR = INFINITY)

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WEATHER RADAR MODEL VELOCITY



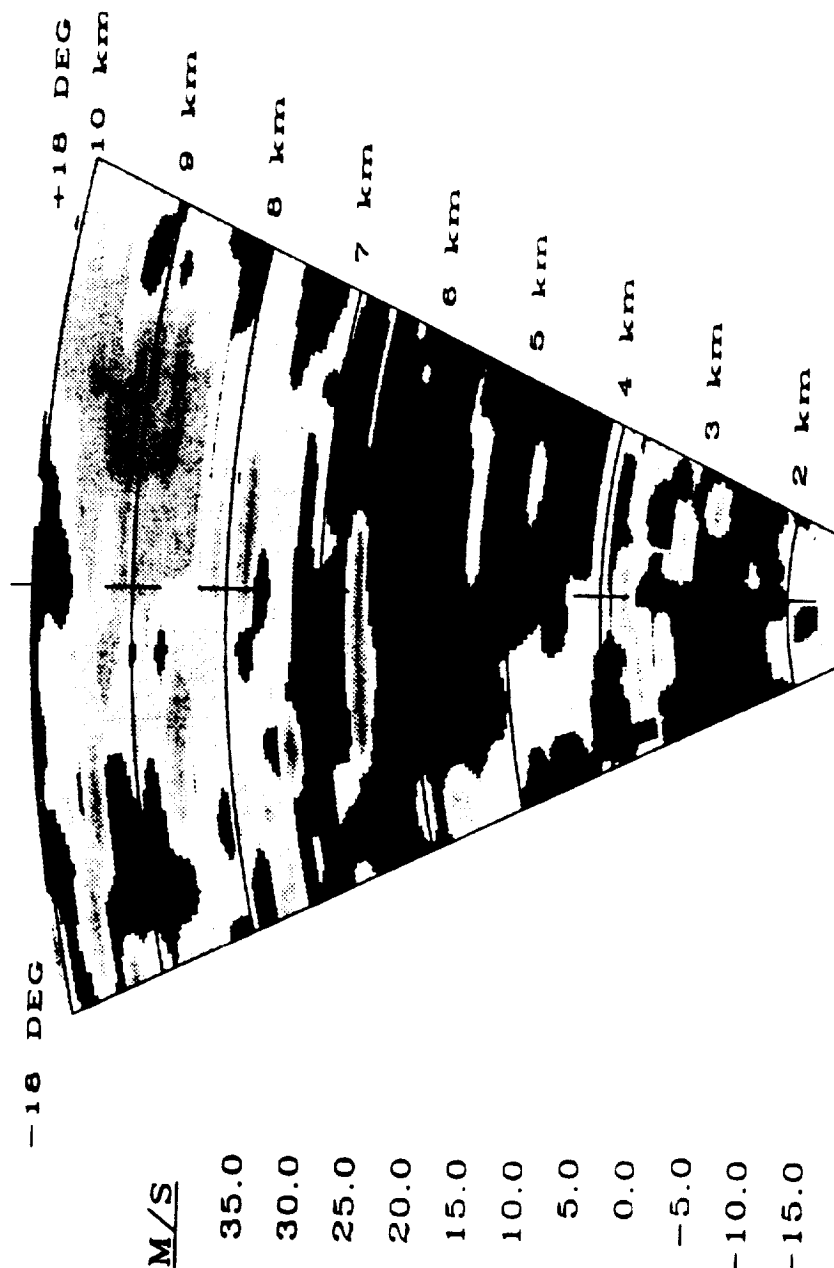
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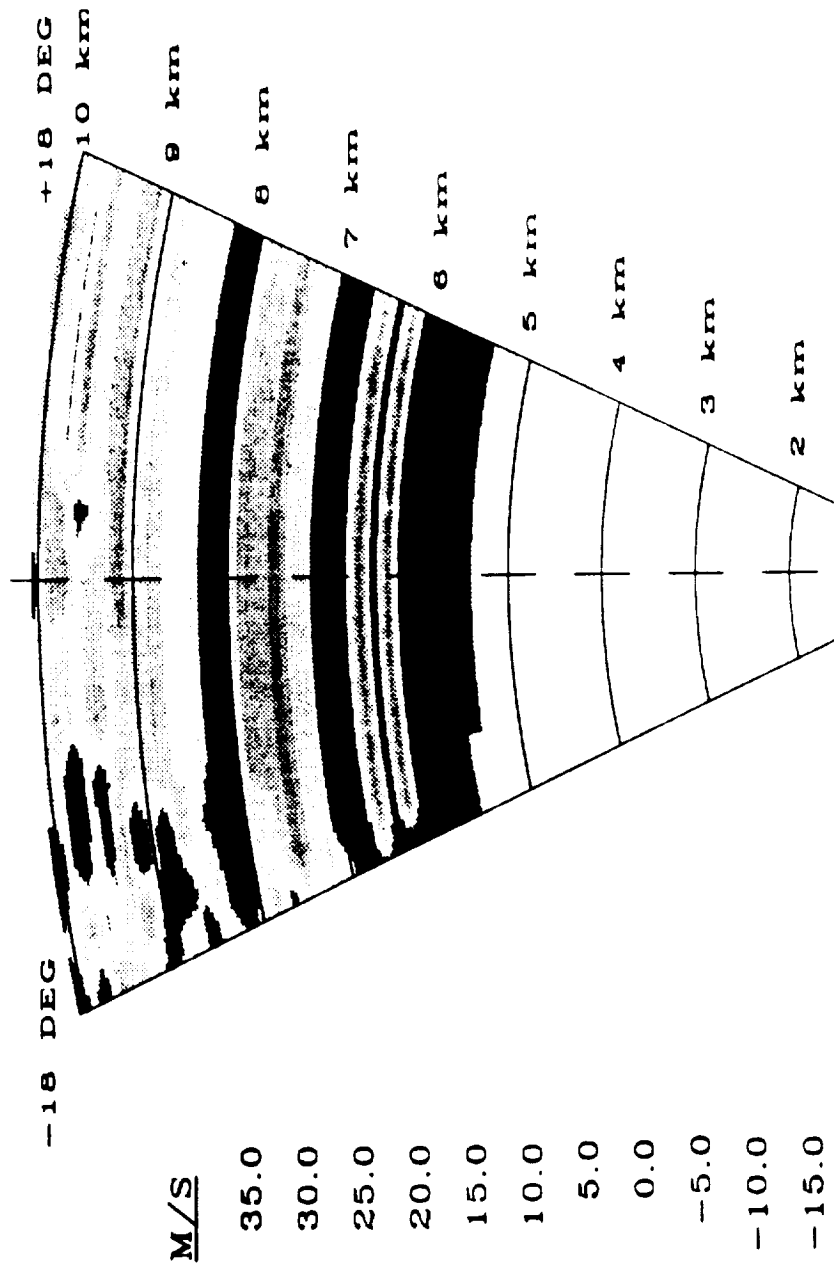


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MUSIC METHOD (SNR=5DB)

WEATHER RADAR MODEL VELOCITY



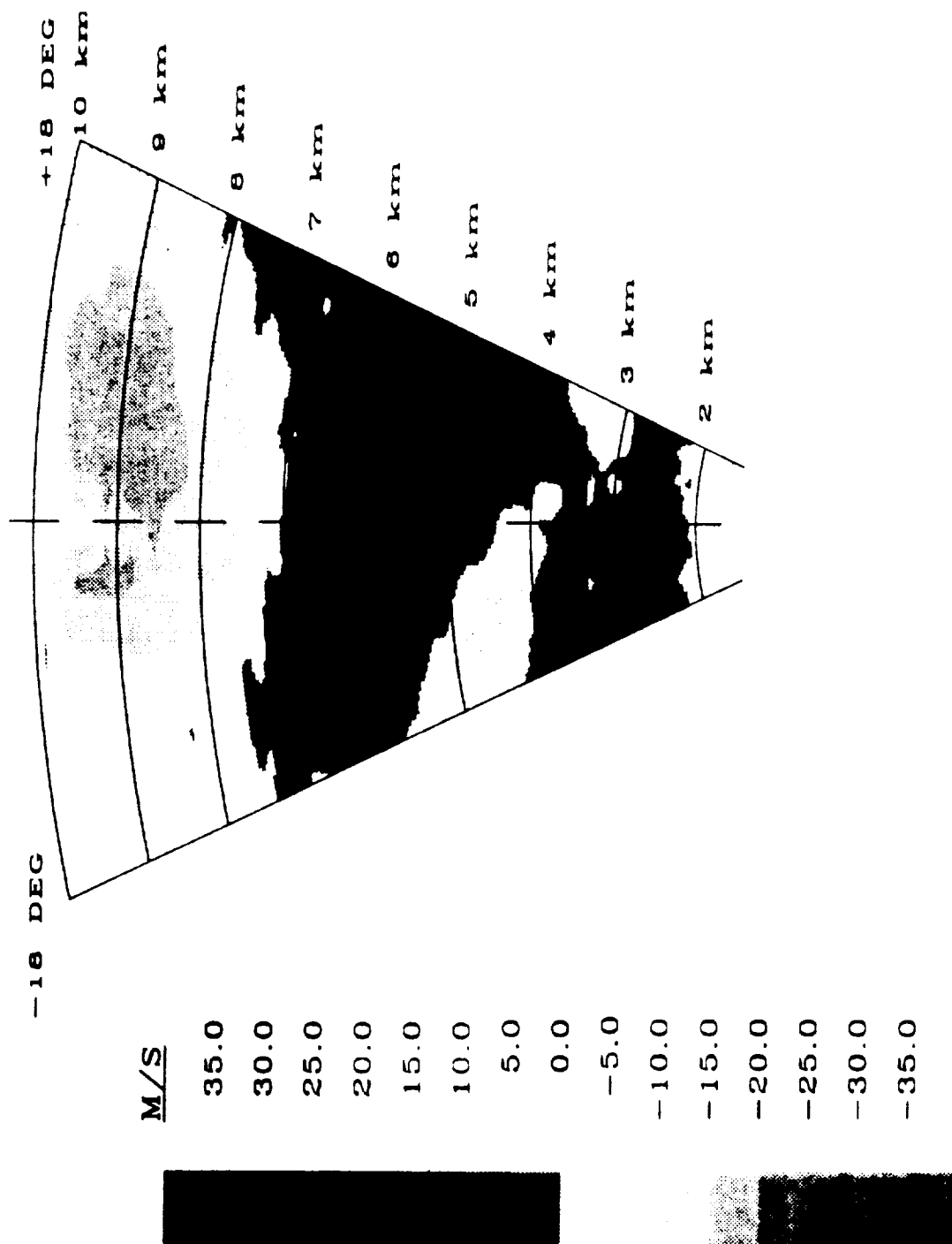
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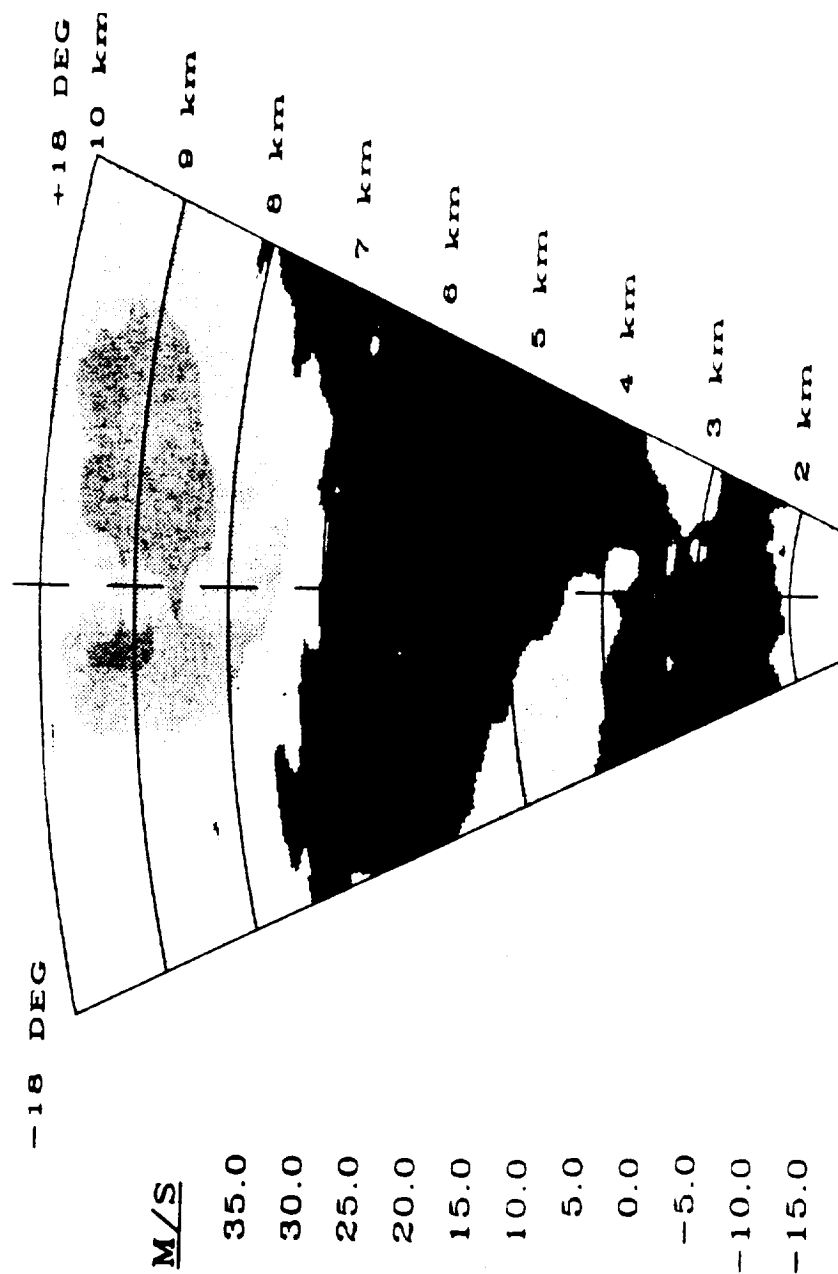
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PERIODOGRAM METHOD (SNR=INFINITY)

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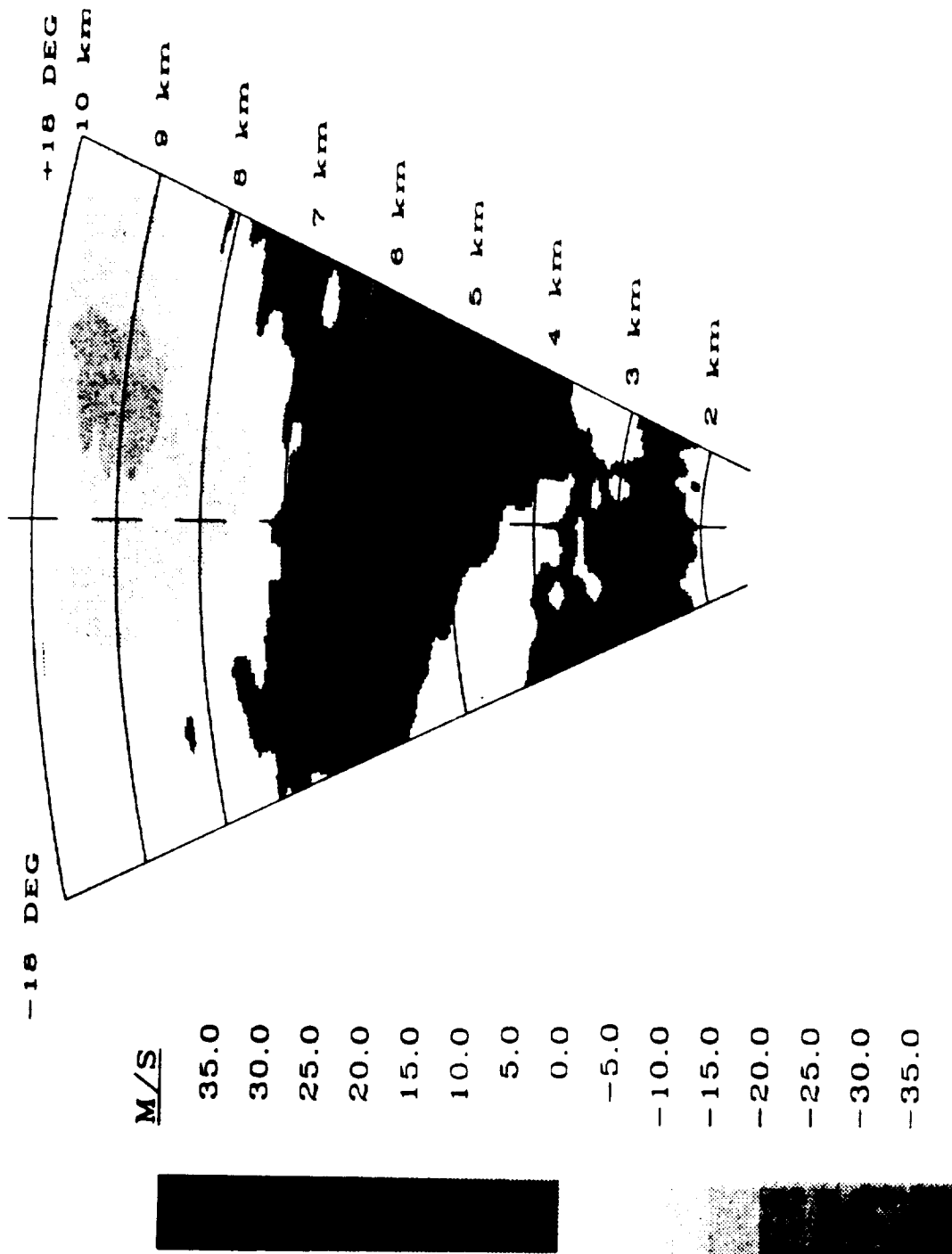
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PERIODOGRAM METHOD (SNR=10DB)

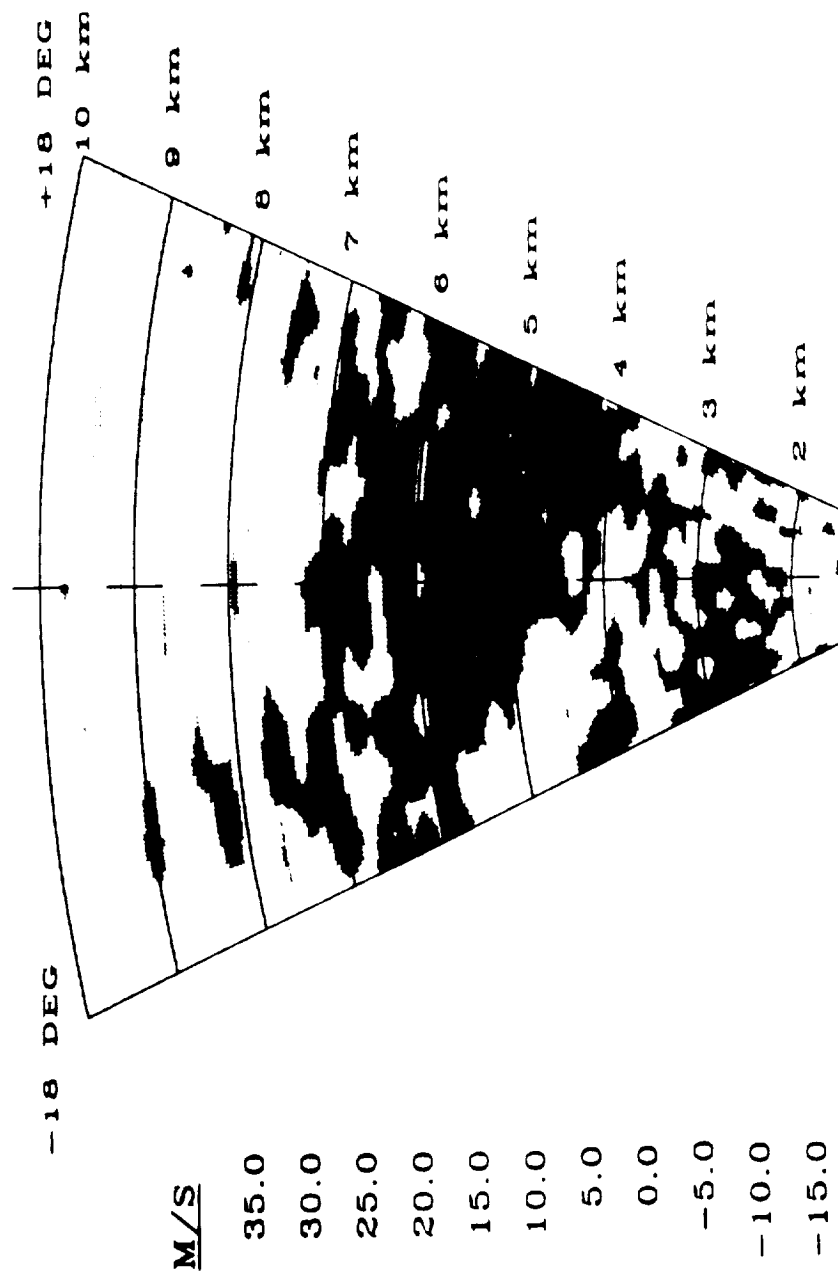
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PERIODOGRAM METHOD (SNR = -5DB)

